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Mapping the conservation priority of migratory shorebird habitat on a dynamic deltaic coast

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ABSTRACT

Shorebird habitat degradation and loss due to high-intensity disturbances from human activities and the negative effects of global climate change in coastal deltas have led to the need to identify and designate priority areas for conservation with different levels of protection. We have proposed an integrated framework and model for the management of priority shorebird habitats in dynamic coastal delta zones (MPH-DC) based on a fuzzy spatial assessment model that incorporates habitat importance and disturbance analyses. By evaluating the relationships between shorebird populations and key ecological habitats, 19 structural factors, including land cover type, vegetation structure, terrain, potential human influence and natural interference, were derived from multi-temporal optical and radar remotely sensed imagery and incorporated into the index system to evaluate habitat conservation priority levels for Charadriidae and Anatidae in the Changjiang estuary, a typical coastal habitat that currently faces enormous challenges but is not yet under dynamic conservation priority management at a large spatial-temporal scale. The use of the MPH-DC framework proved to be effective for evaluating the spatial distribution and conservation priority of habitats in dynamic coastal deltas and for rapidly identifying regions where restoration and priority adjustment are needed, thus enriching broad-scale integrated ecosystem management solutions for coastal deltaic zones.

1. Introduction

Many of the largest deltas in the world are the most important habitats for migratory shorebirds (Bellio and Kingsford, 2013) along the Asian (Iwamura et al., 2014), European and American coastal flyways (Bairlein, 2016). With sea level rise, land reclamation, diking, invasive species introductions and other local human activities, coastal deltaic wetland habitats, such as salt marshes, mangroves, tidal flats, and shallow water, which provide food, shelter and breeding areas to shorebirds, have become increasingly vulnerable to flooding and have been partly converted to agricultural, urban and industrial areas (Nicholls and Cazenave, 2010; Lovelock et al., 2015; Syvitski et al., 2009). Although migratory shorebirds could respond to habitat change by altering their migratory routes (Rakhimberdiev et al., 2011) or timing (Gunarsson et al., 2006), habitat loss and degradation (Studds et al., 2017) in deltas and estuaries are the main factors contributing to sharp declines in migratory bird populations, such as in the Mississippi delta in the USA, the Indus delta in Pakistan, and the Amazon delta in Brazil (Temmerman et al., 2013).

To halt the decline in migratory species and their abundance, several international frameworks aiming to conserve migratory species (Murray et al., 2012) have been formed in recent decades, such as the Ramsar Convention (Kleijn et al., 2014) and the Convention on the Conservation of Migratory Species of Wild Animals (CMS, 2003). Numerous wetlands of international importance, nature reserves, national wetland parks, bird refuges and other types of protected areas have been established to conserve migratory shorebirds in coastal delta areas. However, with high levels of intensive human disturbance and the influence of rapid global climate change, shorebird habitats in coastal delta zones have experienced highly dynamic gains and losses of wetlands and variation in wetland abundance, type, and spatial distribution inside and outside of protected areas. In most cases, wetland losses continue to surpass wetland gains in coastal deltas around the world. To effectively protect migratory shorebirds and their habitats, we need to adopt dynamic conservation management strategies in coastal deltas that coordinate with these rapidly changing environments. The spatially explicit and effective rapid identification of priority areas (Martin et al., 2007; Klaassen et al., 2008; Iwamura et al.,

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2014) should also be implemented to align the habitat protection level with spatial patches or units along the shoreline, covering both unprotected and protected areas.

To map priority areas for shorebirds in coastal deltas, the key is to identify the importance of coastal habitat patches, the distribution of the disturbances that they experience, and the potential effects of such disturbances on the past, present, and future risk to shorebird populations that reflect their exposure, sensitivity and adaptation to disturbance (Metzger et al., 2005). There are some papers on shorebird habitat prioritization, but they have been restricted to individual-based models of animal movement (Klaassen et al., 2008), address relatively simple connections in different habitats at the population level (Martin et al., 2007) or focus on single impacts on migratory shorebirds in coastal habitats. Owing to the complex ecosystem characteristics of coastal deltas, there remain challenges in modelling the variation in shorebird populations along with the dynamic habitat at a spatial-temporal scale and the detailed spatial quantification (Iwamura et al., 2014) of shorebird food, shelter and breeding habitat characteristics.

The spatial and temporal variation in migratory bird habitat in coastal deltas results in field data collection being time-consuming and expensive. Remote sensing is a strong and invaluable tool for quantifying environmental features, such as land cover (Tian et al., 2008), landscape structure (Ungaro et al., 2017), terrain morphology (Clausen et al., 2014), hydrological conditions, and anthropogenic activities (Dong et al., 2013). This technique also has ecological applications (Nagendra et al., 2013; Pettorelli et al., 2014) ranging from habitat delineation (McDermid et al., 2005) to the mapping of specific target areas, e.g., forests (Wulder et al., 2012) and wetlands (Tian et al., 2016). However, remote sensing data alone are insufficient for understanding changes in shorebird habitat (Tett et al., 2013), and process-based habitat analysis models constructed with multi-resource remote sensing imagery can contribute to the definition of habitat priorities considering the species' ecological requirements and distributions (Condet and Dulau-Drouot, 2016). Currently, mid-resolution and multi-resource remote sensing optical and radar data, in particular, can be easily and freely accessed.

Here, we propose an integrated framework and modelling approach to inform the management of priority shorebird habitats in dynamic coastal delta zones (MPH-DC) that combines a habitat spatial importance and disturbance assessment model with remote sensing and GIS (Geographic Information Systems) data. We chose the Changjiang estuary, a dynamic coastal zone, as a case study; this area is one of the most important transit locations for Charadriidae and overwintering sites for Anatidae on the East Asian-Australasian Flyway (EAAF) (Green and Elmberg, 2014). The aims of this study were to (1) construct a synthetic assessment model of coastal habitat importance and disturbances to illustrate the status of shorebird habitat, (2) extract multiple forms of spatial habitat information from multi-temporal optical and radar remotely sensed imagery combined with ecological knowledge, (3) apply an integrated modelling framework to map shorebird habitat priorities on a dynamic delta and identify the coastal zones within the protected areas that require habitat restoration or adjustment of the original level of protection, and (4) identify the zones outside the protected areas where interference control and protective action are needed to improve shorebird survival.

2. Materials and methods

2.1. Study area description

The Changjiang River, Asia's largest river, has the largest drainage area (1.8×10^6 km^2) and the longest length (6300 km) in Asia (Bi et al., 2017). With an average annual sediment discharge of approximately 490 Mt (million tons), as measured over 53 years (1950–2002), the Changjiang River has built a large delta system. The Changjiang deltaic coast (30°40′N-31°53′N, 120°51′E−122°12′E) has rapidly prograded seaward, although the Three Gorges Dam (TGD) has caused the sediment discharged into the Yangtze estuary to decrease by 130 Mt/yr relative to the normal water years of 2001–2002 and may result in further delta erosion (Yang et al., 2014).

Since the Changjiang River estuary is close to Shanghai, one of the most economically active cities in China and around the world, it has been subjected to rapid economic development, with an increase of 12 million inhabitants since 1985. The built-up area has also increased from 185 km^2 in 1985 to 550 km^2 in 2000 and 998 km^2 ha in 2010 (Tian et al., 2016). Furthermore, although approximately 800 km^2 of active intertidal mudflats continue to fringe the delta (Fan et al., 2006), the Second Chinese National Wetland Inventory showed that the coastal wetland in Shanghai declined by 545.19 km^2, representing an annual loss of 1.79% from 2002 to 2012 (Tian et al., 2016). Approximately 10 known invasive plant species occur in Shanghai. Of them, *Spartina alterniflora* is extremely threatening to the coastal wetland system and causes problems for native plants and shorebird communities (Huang et al., 2017).

Even so, some regions remain good wetland environments with various levels of protection, such as internationally and nationally important wetlands, wetland parks, and natural reserves, and attract a large number of migratory shorebirds in comparison to unprotected areas. Charadriidae and Anatidae are the main taxa of migratory shorebirds in the Changjiang estuary and depend upon coastal wetlands during their migration. Members of these families accounted for 47.62% and 30.36%, respectively, of the total number of shorebirds recorded between 2006 and 2010, which was 796,738, and included species in IUCN (International Union for Conservation of Nature) red list categories, such as *Eurynorhynchus pygmeus, Mergus squamatus, Tringa guttifer, Anser erythropus, Anser cygnoides, Anas formosa, Numenius madagascariensis* and *Calidris tenuirostris* (IUCN, 2017). Considering the characteristics of coastline dynamics and that shorebirds avoid large areas of deep-water habitat, we used shoreline buffer analysis to identify coastal habitat zones (Fig. 1) above the 0-m elevation contour (referred to as the Wusong Datum, WD) that included seawater, estuary, intertidal, and terrestrial zones, and we identified approximately 1 km-wide assessment units using the Digital Shoreline Analysis System (DSAS).

2.2. Habitat importance analysis

Important habitats are natural areas along a coastline that provide a wide range of resources for migratory shorebirds including food, breeding areas, and shelter; the availability of such resources often reflects habitat quality (e.g., species abundance and diversity). The purpose of habitat importance analysis is to identify the types, locations and spatial distribution of habitats that shorebirds prefer.

In the Changjiang estuary, previously collected field and satellite tracking data (Fig. 2), which were provided by the Wildlife Conservation Authority, show that Charadriidae prefer shallow ponds in the tidal zone over high-density reed-*Spartina alterniflora* belts or inland artificial wetlands and that they are also fond of mud flats and benthic prey animals such as gastropods, bivalves, crustaceans and small fish. In contrast, Anatidae are often found in open water with some surrounding vegetation, especially abandoned fish ponds, and prefer the seeds, bulbs and roots of *Scirpus mariqueter/Scirpus triqueter* and the tender roots and leaves of other aquatic plants.

We analyzed the behaviour of Charadriidae and Anatidae and found that three elements play an important role in the daily life history of these shorebirds: the wetland habitat and shelter and feeding areas. Therefore, to fully express the importance of habitat, 13 structural factors were selected and integrated into the habitat importance index system (Table 1). The first group of parameters in the index system represented wetland habitat (five factors): (1) aquaculture ponds, (2) water storage areas, (3) drainage channels, (4) intertidal marshes/intertidal forested wetlands/inland marshes and (5) the proportion of

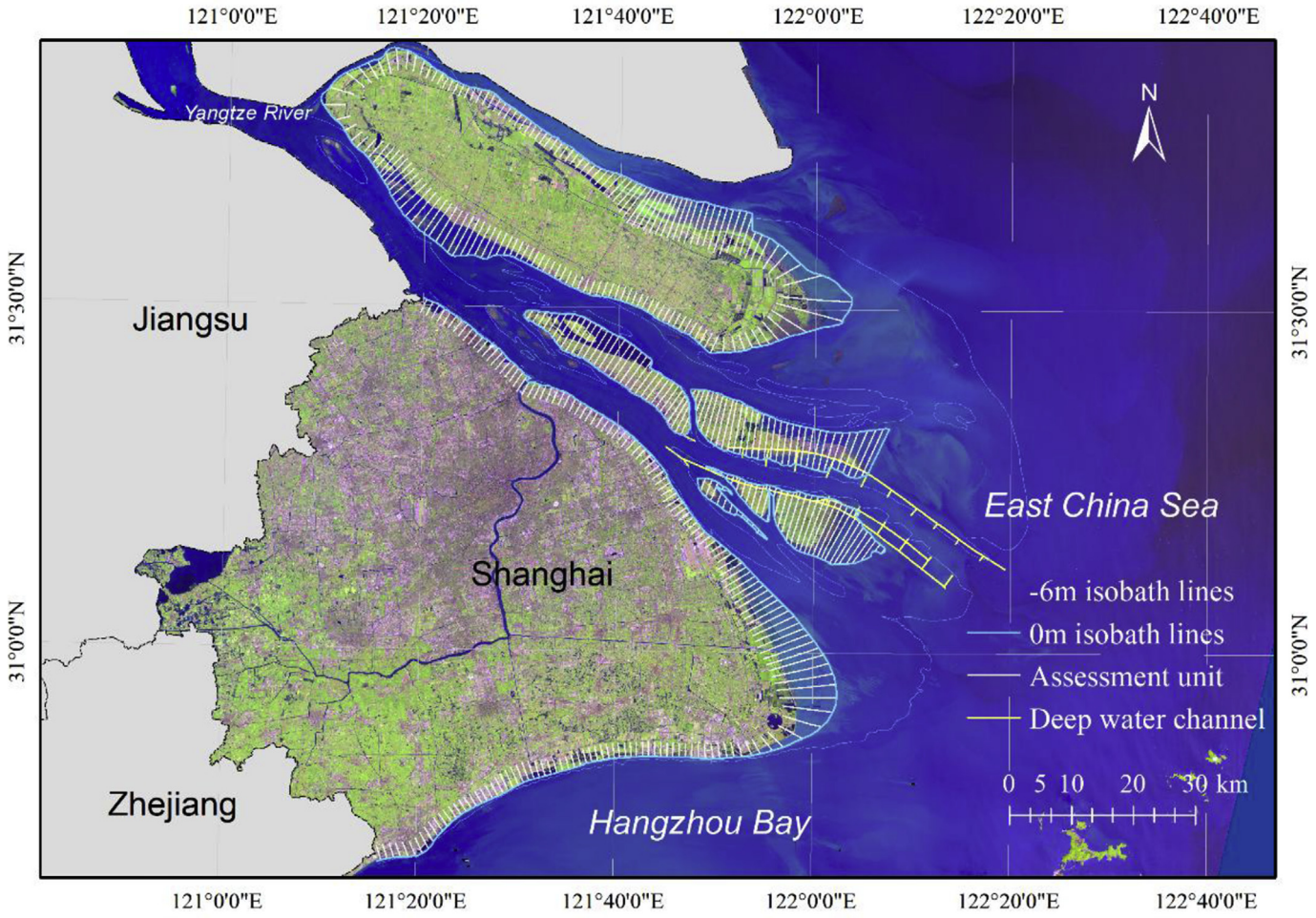

Fig. 1. The geography of the Changjiang coastal delta region, China. The background is a Landsat 8 OLI image (RGB = bands 6, 5, and 2) from August 3, 2015.

shallow water. The second group of parameters represented shelter/breeding conditions (three factors): (6) irrigated land, (7) forest and grassland and (8) a specific shelter plant (*Phragmites australis*). The third group of parameters represented feeding/food conditions (five factors): (9) tidal flat width and (10) soil type (these two factors indirectly represented benthic biomass), (11) submerged vegetation in ponds, (12) salt marsh/marsh vegetation (*Scirpus mariqueter,* which provides bulbs and seeds), and the cofactor (13) tidal creek (due to tidal action, many fish, shellfish, and other benthic resources are brought to the tidal creek, and *Scirpus mariqueter* near the tidal creek can be exposed to the surface or shallow beaches).

Since the coastal wetland ecosystem is a complex system, interrelated with and restricted by nature, the economy and society, the evaluation of coastal wetland ecosystems shows uncertain and fuzzy features. Due to progress in the application of fuzzy theory to ecosystem, we used a fuzzy assessment model (Sarkar et al., 2016) to quantify habitat importance. This process included five main steps: establishing the factor set, determining the set of factor weights, constructing the comment set, building the evaluation matrix and calculating the degree of factor membership (see Appendix A).

Accordingly, the set of factors for the habitat importance analysis was identified based on a habitat importance index system weighted by the Analytic Hierarchy Process (AHP) method (see Appendix B) (Saaty, 1990), and the comment set was composed of different grades. Then, using the trapezoid membership function (see Appendix C), the evaluation matrix was obtained according to the standardized grading standard, and the degree of membership of the factors was determined by multiplying the weight set and the evaluation matrix. We obtained the evaluation grade for each shorebird taxon based on the principle of maximum membership degree and used these values to calculate habitat importance:

$$HI = \sum_{1}^{j} \left\{ \left[max\left(I_{wetland} + I_{shelter} + I_{food}\right)_j \right] p_j \right\} \quad (1)$$

and

$$I = WR = (w_1, w_2, \ldots w_n) \begin{pmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & r_{nm} \end{pmatrix} \quad (2)$$

where *HI* indicates the habitat importance; *I* represents the degree of membership; p_j is the normalized relative proportion of shorebird taxon *j* (here, the relative proportion of Charadriidae or Anatidae is represented by a constant of 0.6 or 0.4, respectively); *W* is the weight set obtained via the AHP method (for the method, see Appendix B, and for the calculation results, see Appendix E); *R* is the evaluation matrix composed of judgement values (r_{nm}); *n* is the factor number (a total of 13); and *m* is the comment number (represented by a value from one to ten).

2.3. Habitat disturbance analysis

Human activities and natural processes can alter habitat conditions for foraging, nesting, or resting during shorebird migration periods. For the low-lying coastal habitats of migratory shorebirds, the impacts caused by environmental change can easily lead to possible gains or losses of species population numbers. Therefore, analyzing the effects of

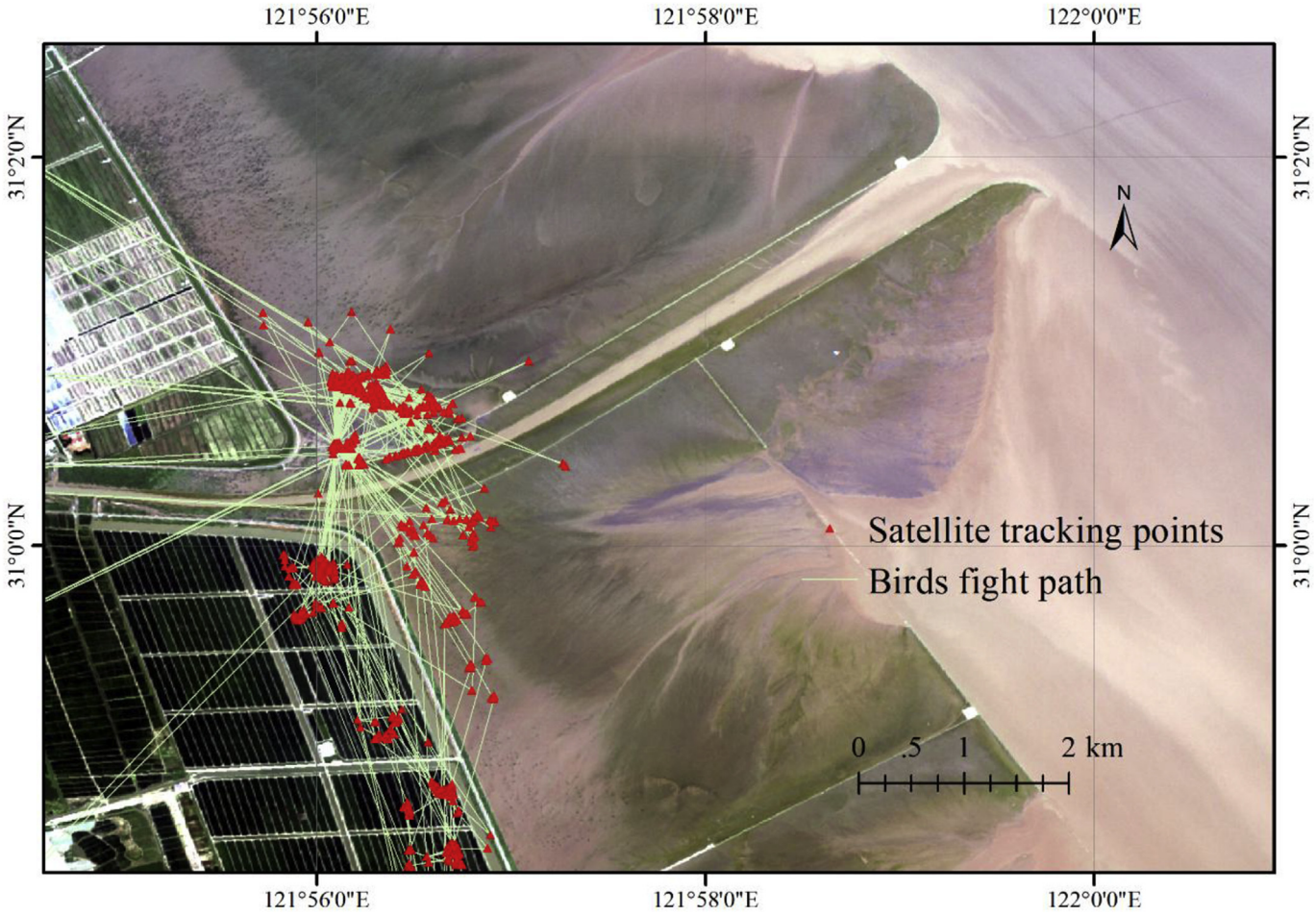

Fig. 2. Map of satellite tracking points and the flight path of *Anas clypeata,* a species of Anatidae, in Nanhui east shoal during the wet season from June to August 2017 using HQBN2513. The background is a GF-1 WFV image (RGB = bands 1, 4, 3) from January 9, 2015.

coastal habitat patch disturbance on past, present and future risk is an important component of conservation prioritization.

In terms of habitat disturbances, infrastructure engineerings, such as urbanization and road construction, greatly affects species habitats and contribute to habitat loss. The risk of collision posed to birds by offshore wind turbines from the increasing extent of wind power farm construction (Plonczkier and Simms, 2012) and habitat degradation from wetland reclamation for fisheries and agriculture (Tian et al., 2016) are also considered to be major disturbance factors. The introduction of invasive species and sea level rise associated with climate change drastically affect wetlands and beaches over time, resulting in a decrease in habitat that threatens shorebird populations and survival rates (Wu et al., 2017).

Based on the disturbance factors mentioned above, the habitat disturbance index system (Table 1) is composed of two parts: a set of disastrous disturbance factors, which can result in rapid and devastating effects, including (14) urbanization, (15) road density, (16) wind power farms, and (17) reclamation, and a set of chronic disturbance factors that have persistent but not significant impacts on the habitat, which is composed of (18) invasive species introduction (*Spartina alterniflora*) and (19) sea-level rise.

The total disturbance value can also be acquired from the fuzzy assessment model and is defined as *HD*. As mentioned previously, care should be taken when considering each factor and its weight; here, the only difference is that the differential impacts of these disturbances on different shorebird species should be ignored because the disturbance receptor is the habitat instead of the birds.

$$HD = max\ (D_{disastrous} + D_{chronic}) \tag{3}$$

and

$$D = WR = (w_1, w_2, \ldots w_n)\begin{pmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & r_{nm} \end{pmatrix} \tag{4}$$

where *HD* indicates the habitat disturbances; $D_{disastrous}$ represents the disastrous disturbances; and $D_{chronic}$ represents the chronic disturbances.

2.4. Quantification with remote sensing

Due to the variation in factor requirements and the benefits of data diversity, multi-resource remote sensing data were acquired, processed, and applied (Table 2). Among the data sources, the aerial photographs have the high spatial resolution, but the low temporal resolution cannot guarantee information diversity. The multi-band Landsat satellite images can effectively show changes in objects but are limited by their intermediate spatial and temporal resolution. The GF satellite images have better temporal resolution and multiple levels of spatial resolution, but their spectral resolution is deficient. Radar data, such as those provided in Sentinel images, are sensitive to the moisture properties of the vegetation and surface, but because radar penetrates clouds, they are particularly useful where cloud cover is a problem.

The preprocessing of these data was conducted using the ENVI 5.3 software and SNAP (Sentinel Application Platform). The procedures used for the optical images included geometric correction, FLAASH (Fast Line-of-Site Atmospheric Analysis of Spectral Hypercubes)

Table 1
The evaluation index system for determining migratory shorebird habitat priority.

1st-level evaluation factor set	2nd-level evaluation factor sets	Single evaluation factors
Habitat importance	Wetland habitat (coastal\inland \human)	Aquaculture ponds u_1
		Water storage areas u_2
		Drainage channels u_3
		Intertidal marshes/intertidal forested wetlands/inland marshes u_4
		Proportion of shallow water u_5
	Shelter/Breeding	Irrigated land u_6
		Forest and grassland u_7
		Specific shelter plant (*Phragmites australis*) u_8
	Feeding/Food	Benthic biomass (tidal flats width) u_9
		Benthic biomass (soil type) u_{10}
		Submerged vegetation in ponds u_{11}
		Salt marsh/marsh vegetation (*Scirpus mariqueter*) u_{12}
		Tidal creek density u_{13}
Habitat disturbance	Disastrous disturbances	Urbanization (2005–2015) u_{14}
		Road density (2005–2015) u_{15}
		Wind power farm u_{16}
		Coastal reclamation (2005–2015) u_{17}
	Chronic disturbances	Invasive introduction (*Spartina alterniflora*) (2005–2015) u_{18}
		Rate of sea level rise (1980–2015) u_{19}

atmospheric correction, and radiometric calibration, while the processing of the Sentinel-1 images included radiometric calibration, single-product speckle filtering, coregistration and range-Doppler terrain correction. In addition, the processing of high-density terrain point cloud data obtained from a single-beam sounding system and Trimble R8 GPS satellite positioning system included triangulated irregular network (TIN) and digital elevation model (DEM) generation.

According to the evaluation indexes of habitat importance and disturbance, we extracted the factors from the remote sensing data using the POK (pixel-object-knowledge) classification strategy (Chen et al., 2014), which involves the hierarchical extraction of different objects. With the exceptions of soil type data, which were obtained through field surveys, and sea-level rise rate data, which were obtained from the China Sea Level Bulletin (SOA, 2015) and the Intergovernmental Panel on Climate Change Fifth Assessment Report (AR5) (IPCC, 2014), we used aerial photographs to define habitat factor boundaries based on the OBIA (object-based image analysis) method using eCognition 9.0 software. In addition, by calculating indexes from the Landsat images, such as the clay minerals ratio (Drury, 1993), NDBI (normalized difference built-up index) (Zha et al., 2003), NDWI (normalized difference water index) (Gao, 1996), and NDVI (normalized difference vegetation index) (Tucker, 1979), a set of attributes was obtained that included spectra, geometry, texture and context. Using the CART (classification and regression tree) algorithm, these attributes were used to help automatically classify the main habitat factors (Figs. 3–5) and calculate the proportion and the percentage of change in related factors, and further, they facilitated factor trend analysis using the scenario obtained with Dinamica EGO (Environment for Geoprocessing Objects) (see Appendix D), a well-documented cellular automata model. In addition, using two bands indicative of water permeability (the blue and green optical bands), we obtained the relative water depth for the shallow water region using the bottom albedo-independent bathymetry algorithm from the GF-1 WFV satellite image.

Table 2
List of multi-source remote sensing data used for index quantification.

System (sensor)	Multispectral bands (no.)	Spatial resolution (m)	Revisit time (days)	Data source	Data processing	Habitat index quantification
Aerial imagery	4	0.5		Obtained in 2015	Object segmentation	a) The area proportions were calculated to quantify the factors of aquaculture ponds, water storage areas, drainage channels, salt marsh vegetation, irrigated land, forest and grassland, width of tidal flats, submergent vegetation in ponds and tidal creek. b) The changes in area proportion were calculated to quantify the factors of urbanization, road density and coastal reclamation. c) The number of wind power farms was calculated.
Landsat OLI (Operational Land Imager)/ETM + (Enhanced Thematic Mapper plus) satellite images	7	30	16	Obtained on August 15, 2005 and March 12 and August 3, 2015. Downloaded from the United States Geological Survey Data Center (http://glovis.usgs.gov/)	Object classification based on spectra, geometry, texture and context attributes, which were obtained by calculating bands: Clay Minerals Ratio, NDBI, NDWI and NDVI	
GF-1 WFV (Wide Field of View) satellite image	4	16	4	Obtained on January 9, 2015. Downloaded from the China Centre for Satellite Data Resources and Application (http://www.cresda.com/)		
Sentinel-1 IW (Interferometric Wide Swath) images	1	5 × 20	12	Obtained on November 29, August 25 and September 18, 2015. Downloaded from Copernicus Open Access Hub (https://scihub.copernicus.eu/)	Multi-seasonal band synthesis	The area proportions were calculated for the factors of *Phragmites australis*, *Scirpus mariqueter* and *Spartina alterniflora*.
High-density terrain point cloud data				Single-beam sounding system and Trimble R8 GPS satellite positioning system	Bottom albedo-independent bathymetry algorithm	The average relative water depth was calculated for the factor of shallow water proportion.

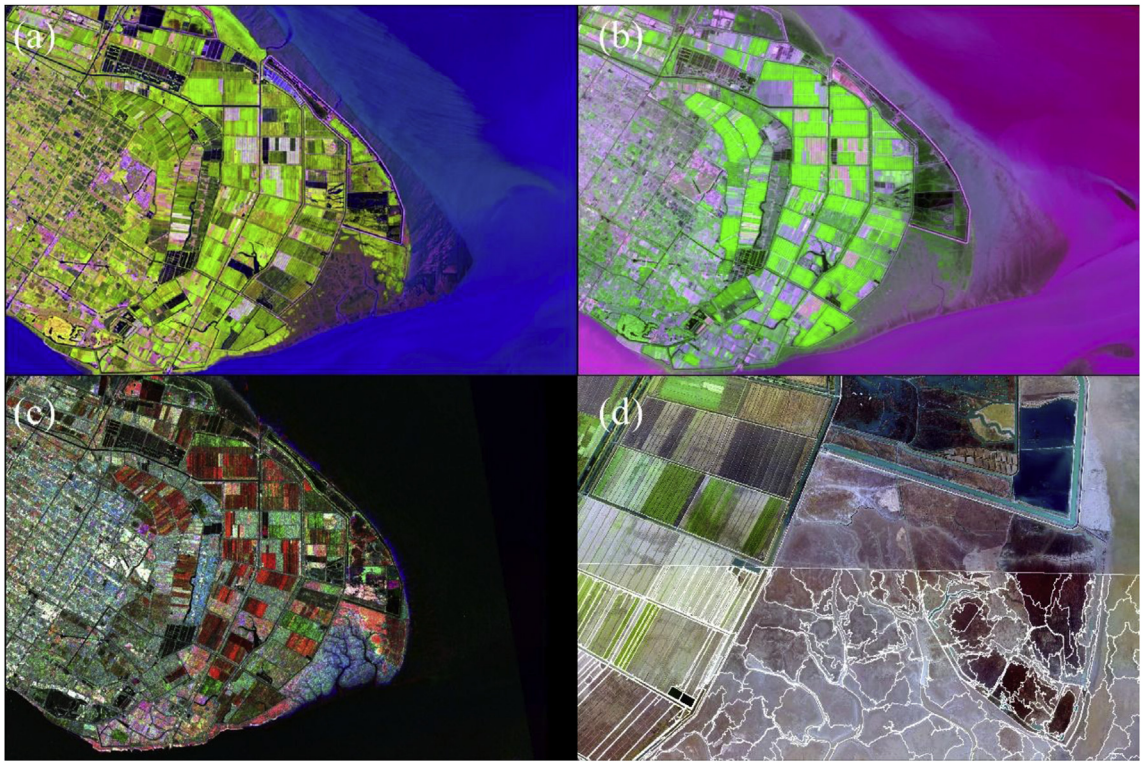

Fig. 3. Multi-source remote sensing data for (a) a Landsat 8 OLI image from August 3, 2015 (RGB = bands 6, 5, 2), (b) a GF-1 WFV image from January 9, 2015 (RGB = bands 1, 4, 3), (c) a Sentinel-1 IW image (RGB = VV polarization band from November 29, August 25, and September 18, 2015), and (d) the aerial image segmentation result from 2015 (RGB = bands 3, 2, 1) using a segmentation scale of 350, with spatially weighted parameters of 0.20 for shape and 0.50 for compactness.

2.5. Conservation priority mapping

Habitat importance is the internal manifestation of habitat quality, which is also subject to external pressures from disturbances. The combination of these internal and external factors can serve as an important reference for habitat conservation and provide an overview of the status of shorebird habitat. However, if the habitat is very well protected, then conservation management will be more effective than in areas lacking a foundation for protection.

Therefore, to generate a dynamic protection strategy, the current protection status, which can include many natural forms of protection, play different roles in the protection system and serve various purposes, should be considered. For existing protected areas, we can adjust the level of protection and develop dynamic strategies to improve habitat management, and for unprotected areas, we can establish new forms of protection for high-priority regions, thus addressing habitat protection vulnerabilities. This dynamic protection strategy can be generated by overlay analysis of maps of habitat importance, habitat disturbance and the types of protection as follows:

$$MPH = Overlay\ (HI,\ HD,\ HP) \quad (5)$$

where *MPH* indicates the management priority level for habitat conservation; *HI* represents habitat importance; *HD* represents habitat disturbance; and *HP* represents the level of habitat protection and includes national parks, nature reserves, landscape parks, protected landscape areas, Natura 2000 areas, natural monuments, documentation sites, ecological areas, landscape-nature complexes, and the protection of plant, animal and fungal species, which is graded from one to ten. The specific criteria and strategies for the overlay analysis are shown in Table 3.

3. Results

3.1. Spatial assessments

The value of migratory shorebird habitat on the coast of the Changjiang delta differed among the study areas, as shown in Fig. 6. Habitat importance (Fig. 6a) was relatively high in the eastern offshore regions, such as Chongming east beach and north beach, Jiuduansha shoal and Nanhui east beach, while the level of disturbance (Fig. 6b) in these areas was lower, except at Chongming north beach. The south bank of Changjiang also exhibited high disturbance intensity. For the level of habitat protection, the map (Fig. 6c) displays the spatial distribution of different forms of natural protection in the study area and indicates that some regions with important habitat, such as Chongming east shoal, are in a protected state.

The map overlaying habitat importance, disturbance and protection level shows that the habitats of high conservation priority are distributed both inside and outside the protected areas (Fig. 6d), which indicates that the original levels of protection were not sufficient for some habitats and that further protection should be initiated for high-priority habitats, such as Hensha east beach and Nanhui east beach. For habitats within protected areas that are of low importance and subject to low disturbance, such as the southern part of the east beach of Chongming, habitat restoration is necessary to improve habitat quality, while close monitoring and adjustment of the original protection level

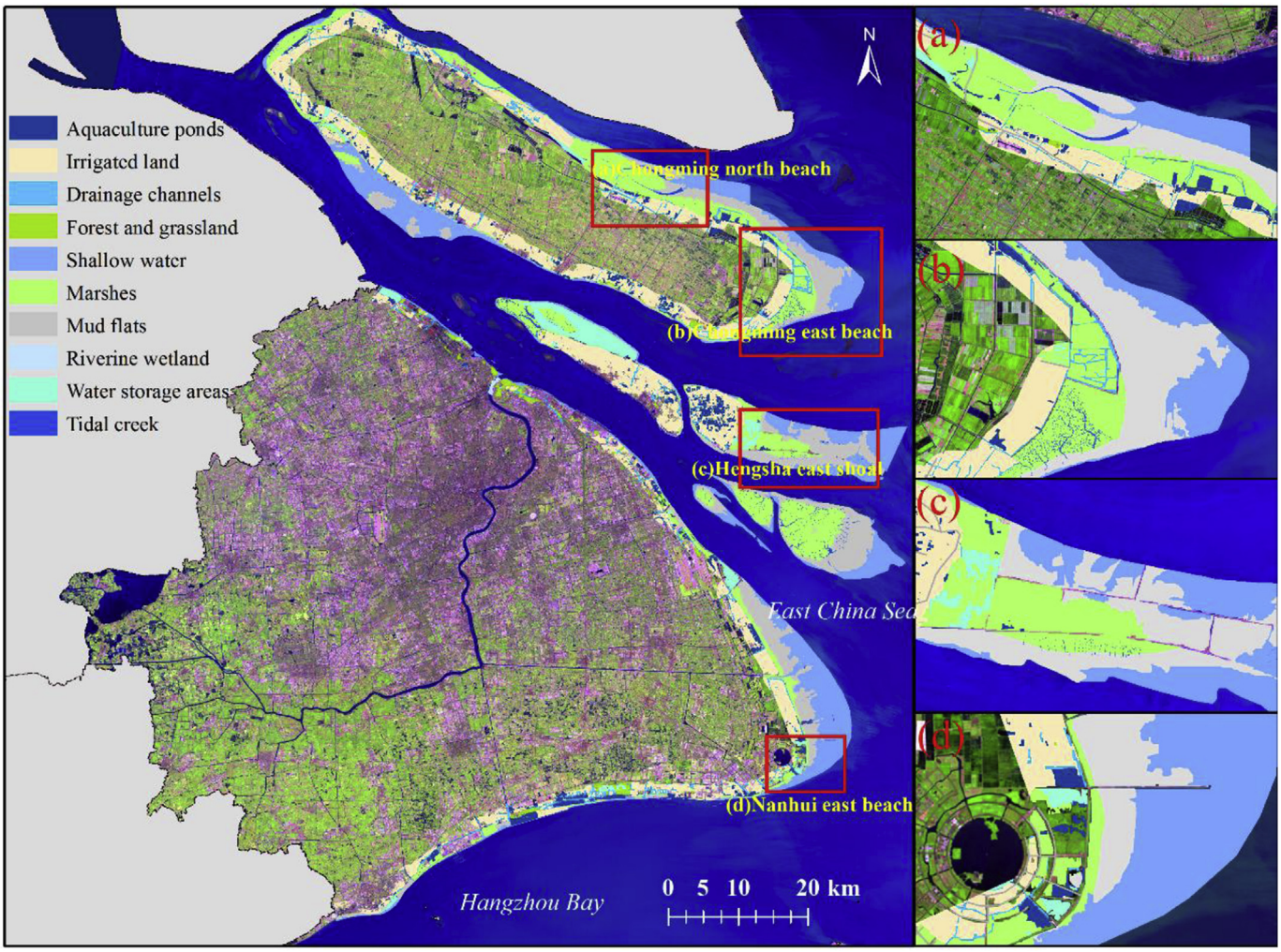

Fig. 4. Map of the shorebird habitat importance factors. The background is a Landsat 8 OLI image (RGB = bands 6, 5, and 2) from August 3, 2015.

are recommended for habitats within protected areas of low importance that are subject to high disturbance, such as some areas of Qingcaosha Reservoir on Chanxing Island. In addition, habitat within protected areas that is subject to low disturbance but is of high importance may require close monitoring but little active intervention, unless an increase in disturbance necessitates an intense, active protection strategy.

3.2. Statistical analysis

Most of the migratory shorebird habitat in dynamic coastal deltas is significantly correlated with land cover type, vegetation structure, terrain, potential human influence and natural interference (Table 1). These factors are directly related to habitat importance and habitat disturbance, which further synthetically determine habitat conservation priority. In terms of habitat importance (Table 4), we found that approximately two-thirds of the region showed a low level (less than three) of habitat importance (119,123 ha), while only 9% (17,206 ha) of the region showed a very high level (greater than seven) of habitat importance. The proportion of the region subject to high and very high levels of habitat disturbance (greater than five) accounted for 21% (38,432 ha), while areas with low levels of disturbance dominated the study region, accounting for approximately 73% (136,291 ha).

In addition, although the overlay analysis showed that the protected areas occupied 30% of the total area, the results indicated that 8% of the total protected area, approximately 15,422 ha, required some measures to further protect shorebird habitats. Of this, the amount of area requiring intense active protection, enhancement and restoration, and priority adjustment and close monitoring was 3722 ha, 9444 ha and 2256 ha, respectively. For the unprotected areas (70% of the total area), the amount of habitat with high importance and low disturbance, i.e., potential protected areas, was 13,602 ha, which needs to be improved, and the corresponding disturbances should be managed and controlled.

4. Discussion

4.1. Ecological remote sensing outlook

Because remote sensing data can be easily accessed, GIS and remote sensing technology can be used as a primary means for the medium-to long-term analysis of habitat trends (Pringle et al., 2009). For example, Landsat images, one of the most widely used forms of remote sensing data, have been the major data source for habitat monitoring, providing detailed data on changes in habitat quality before and after conservation designation and quantifying important fragmentation processes

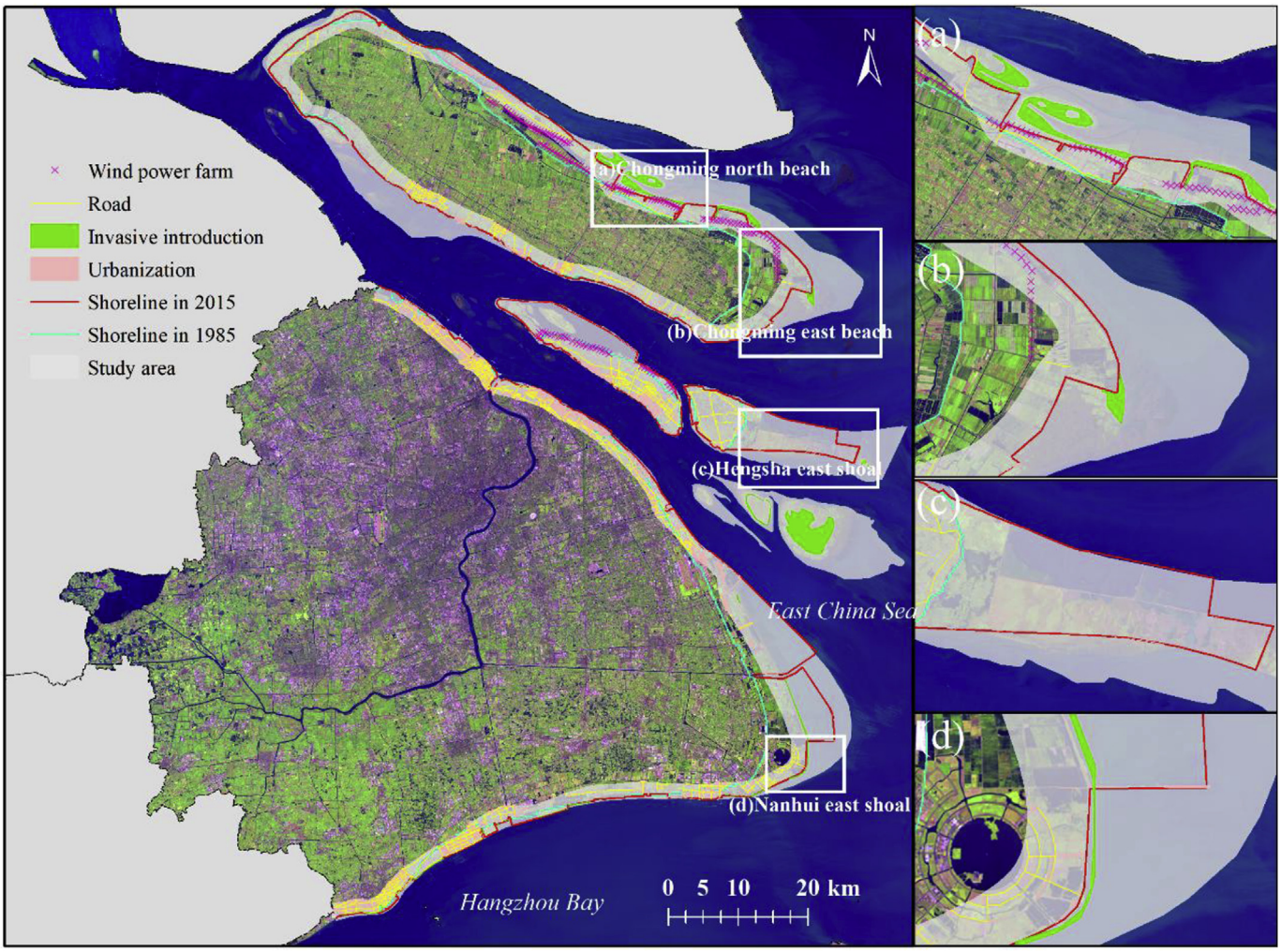

Fig. 5. Map of the shorebird habitat disturbance factors. The background is a Landsat 8 OLI image (RGB = bands 6, 5, and 2) from August 3, 2015.

Table 3
The specific criteria and strategies for the overlay analysis.

Strategy	HI	HD	HP	The description of MPH
1	High (≥ 5)	Low (≤ 3)	N	Potential protected areas
2	High (≥ 5)	High (≥ 5)	Y	Intense active protected areas
3	Low (≤ 3)	Low (≤ 3)	Y	Enhancement and restoration areas
4	Low (≤ 3)	Very high (≥ 7)	Y	Adjustment and close monitoring areas

N indicates the area that has no form of protection, and Y indicates the existing protected area.

and changes in connectivity (Adamo et al., 2016; Kleijn et al., 2014; Nagendra et al., 2013).

However, although GIS and remote sensing technology can assist in habitat conservation and management with up-to-date spatial information, the variables extracted from a single remote sensing image usually represent instantaneous measurement values, ignore extreme values of critical factors, and cannot reflect the overall ecological characteristics. For example, it is difficult to directly identify the maximum exposure area of mud flats using images with medium temporal resolution because of tidal impacts. Furthermore, it is difficult to effectively determine vegetation types with high precision from images with low spatial resolution images, while it is not possible to extract multiple objects from images with high spatial resolution due to the lack of spectral information.

Combining multi-source data can prevent these problems and makes the extracted information more accurate and comprehensive. For this purpose, the GF-1 image with a high revisitation rate facilitated the extraction of tidal flat data, and the Sentinel-1 image data from several seasons enabled us to better distinguish vegetation in this study. Certainly, the ecological applications for multi-source remote sensing are very promising and not limited to those listed above. LiDAR data and hyperspectral data can provide highly accurate digital characteristic information for aquatic vegetation at a fine resolution, such as its height and density (Adamo et al., 2016), and such information is useful for improving habitat discrimination. The combination of these data with GIS spatial analysis allows factors significantly influencing habitat selection to be precisely integrated at a large spatial scale (Pringle et al., 2009). In addition, as approaches used for data collection, in situ observation carried out by the construction of a microelectromechanical observation system and UAV (unmanned aerial vehicle) observation can also play important roles in future applications, benefitting the detection of changes in the three-dimensional structure of habitats (Tiner et al., 2014).

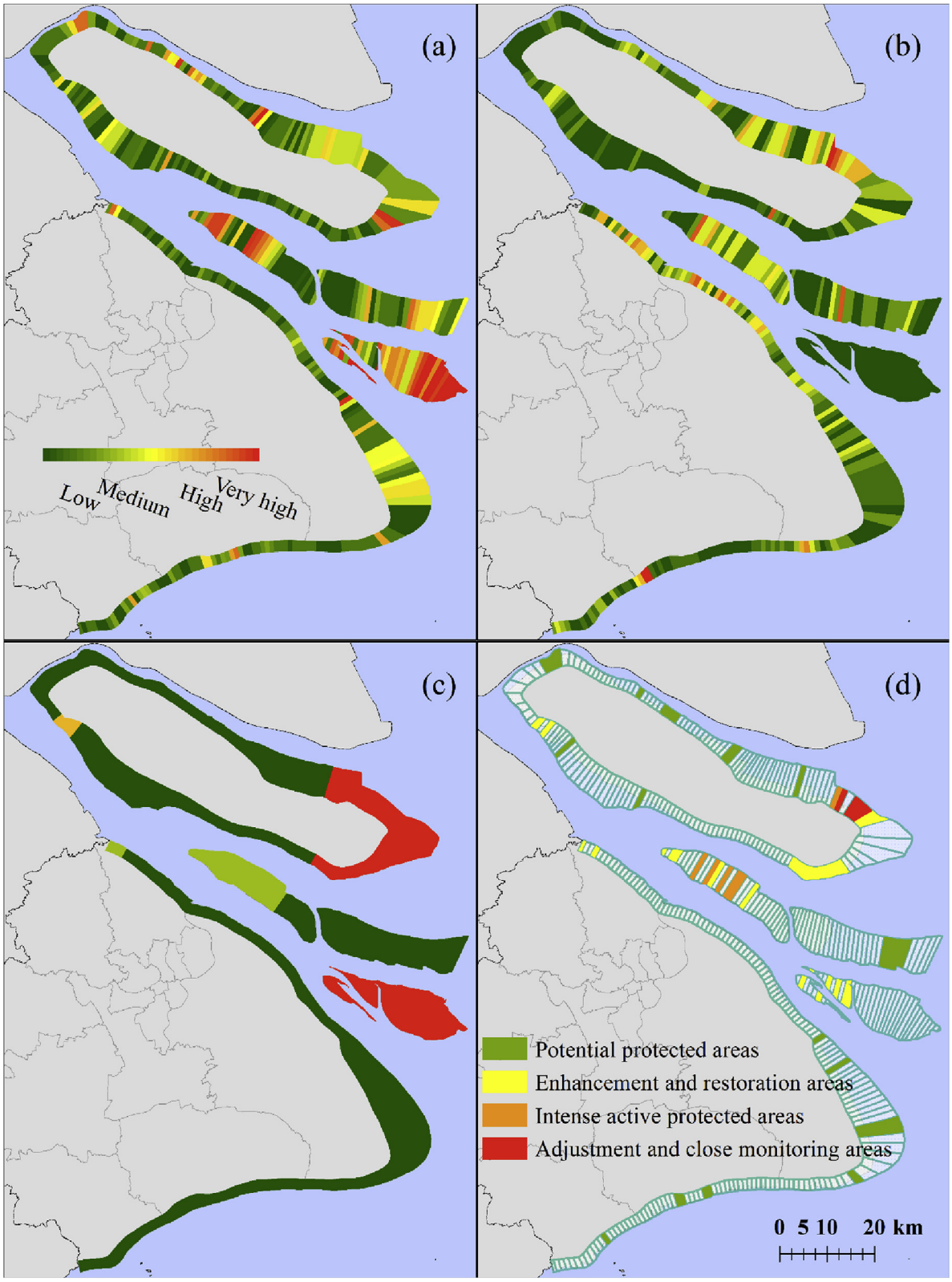

Fig. 6. Map of (a) habitat importance, (b) habitat disturbance, (c) habitat protection level and (d) overlay analysis results for four management strategies.

Table 4
Area (ha) of habitat importance, disturbance and protection.

Level (1–10)	Low (≤ 3)	Medium (> 3 and < 5)	High (≥ 5 and < 7)	Very high (≥ 7)
HI	119,122.56	25,706.75	24,564.73	17,206.14
HD	136,291.52	11,876.38	26,120.02	12,312.26
HP	131,094.55	12,347.13	1421.25	41,737.24

4.2. Habitat importance and disturbances

According to the analysis of migratory shorebird habit, habitat quality mainly depends on the factors necessary for the survival of shorebirds, including wetland habitats, shelter and the food supply. In addition, different shorebird species have different habitat preferences, indicating that the sensitivity of shorebirds to habitat can lead to differences in habitat selection and that multiple habitat combinations can affect habitat importance. Therefore, the number of core habitat types and their proportion in an analysis unit are the direct manifestation of habitat importance. In this paper, the degree of membership is used as the basis for the judgement of importance and is expressed as the multiplicative-additive operator for the weight set and the evaluation matrix; it reflects the degree of preference for different habitat structures, including habitat types and their proportions.

As a receptor in nature, habitats not only provide "output" for shorebird survival but also suffer the "input" of disturbances from the outside. In addition, the possible disturbances from the outside world usually have a certain intensity and temporal-spatial effects and exacerbate the dynamics of habitat succession, causing ecosystem instability. The impacts from disturbances from urban expansion, reclamation, and road and wind power farm construction are disastrous and essentially permanent, while invasive species introductions, sea level rise and coastal subsidence and erosion can be considered to be chronic disturbances, affecting habitat importance over time. Integrating the disastrous and chronic disturbances, risk trends and vulnerability responses can reflect uncertainty from habitat sensitivity, exposure, coping capacity and adaptation.

4.3. Habitat conservation management

On dynamic delta coasts, human activity and natural interferences have led to the loss of ecosystem function for migratory shorebirds and affect their population structure and survival (Troupin and Carmel, 2016). Invariable habitat conservation management policies may be the major issue in management, as they cannot keep up with the changing habitats and may even have the opposite effect. Some studies show that the establishment of national parks can result in accelerated population growth rates in their surrounding areas and increase the fragmentation of natural areas (Gimmi et al., 2011; Troupin and Carmel, 2016).

Facing the inefficiency of protection policies and determining how to balance shorebird habitat "supply" and "demand" and dynamically adjust conservation priorities are the key factors to consider in policy-making. In the proposed MPH-DC framework, the fuzzy assessment model and the Dinamica-EGO model were coupled and used to calculate the "supply" of habitat, which allowed for the analysis and application of a variety of habitat parameters, including mid- and long-range historical and predicted factors. Meanwhile, the integration of remote sensing data made the framework appropriate for any coastal zone regardless of the scale.

For China, since the importance of waterfowl-associated wetlands for other wildlife species is acknowledged, the prioritization of migratory shorebird management would help to scientifically define the red line boundaries for new policies of China's ecological red line division. This definition is also the basis for the establishment of other management strategies, such as ecological security early-warning, ecological compensation, and ecological security protections. Certainly, the conservation of single sites along migratory flyways cannot completely solve the problem of shorebird protection, as threats in any part of an annual cycle can affect the entire population of a migratory species (Runge et al., 2015). Hence, with the shared responsibility to protect migratory species, the MPH-DC framework for priority management strategies provides insight into efficient conservation planning on the coastline of the species' migratory network.

5. Conclusions

Degradation and loss of shorebird habitats in coastal deltas have led to the need to identify and designate priority areas for conservation with different levels of protection. This study provides a rapid approach to evaluate the spatial distribution and conservation priority of habitats in dynamic coastal deltas and to identify regions where restoration and priority adjustment are needed. Based on modelling using multi-resource remote-sensing imagery, we mapped habitat conservation priorities and then overlaid the current levels of habitat protection. The proposed conservation management strategy provides cost-effective guidance for habitat restoration or modification of protection strategies, thus enriching broad-scale integrated ecosystem management solutions for coastal delta zones.

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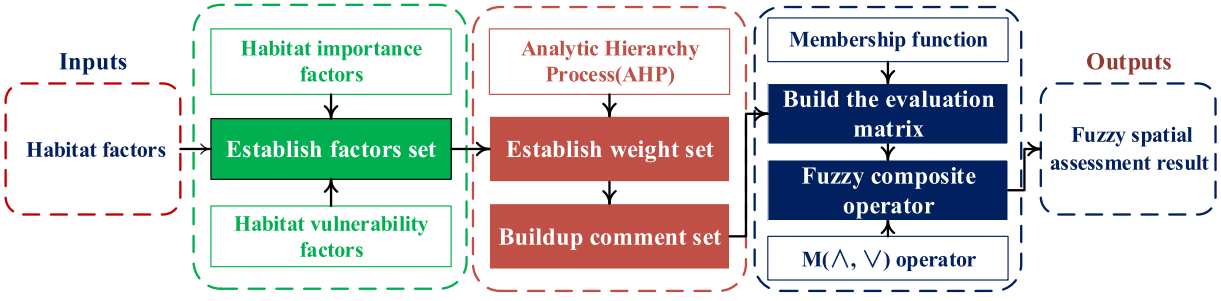
Appendix A. Outline of the fuzzy spatial assessment model



Appendix B. The analytic hierarchy process

Step 1: Obtain the reference scales of importance between two factors.

Scales of reference importance	Explanation
1	U_i is equally important to U_j
3	U_i is slightly more important than U_j
5	U_i is more important than U_j
7	U_i is much more important than U_j
9	U_i is substantially more important than U_j
2,4,6,8	Intermediate values between adjacent scale values

where U_i and U_j are evaluation indicators.

Step 2: Build judgement matrix U based on Step 1.

$$U = \begin{bmatrix} U_1/U_1 & U_1/U_2 & \dots & U_1/U_n \\ U_2/U_1 & U_2/U_2 & \dots & U_2/U_n \\ \vdots & \vdots & \ddots & \vdots \\ U_n/U_1 & U_n/U_2 & \dots & U_n/U_n \end{bmatrix} \tag{B1}$$

Step 3: Check the consistency of the results.

$$\mathrm{C}_R = C_I/R_I \tag{B2}$$

and

$$\mathrm{C}_I = (\lambda_{max} - n)/(n-1) \tag{B3}$$

where λ_{max} is the maximum eigenvalue of the matrix U, and R_I is random consistency index obtained from the following table. Generally speaking, when the C_R is less than 0.10, the judgment matrix has satisfactory consistency; otherwise, the judgment matrix should be adjusted.

The order of U	1	2	3	4	5	6	7	8	9	10	11	12
R_I	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48

Appendix C. The trapezoid membership function in the fuzzy spatial model

$$\mathrm{r}_{i1} = \begin{cases} 1, & x_i \le S_{i1} \\ \frac{I_{i1} - x_i}{I_{i1} - S_{i1}}, & S_{i1} < x_i < I_{i1} \\ 0, & x_i \ge I_{i1} \end{cases} \tag{C1}$$

$$\mathrm{r}_{in} = \begin{cases} \frac{x_i - S_{i(n-1)}}{I_{i(n-1)} - S_{i(n-1)}}, & S_{i(n-1)} < x_i < I_{i(n-1)} \\ 1, & I_{i(n-1)} \le x_i \le S_{in} \\ \frac{I_{in} - x_i}{I_{in} - S_{in}}, & S_{in} < x_i < I_{in} \\ 0, & x_i \ge I_{in} \text{ or } x_i < S_{i(n-1)} \end{cases} \tag{C2}$$

$$\mathrm{r}_{im} = \begin{cases} 0, & x_i \le S_{i(m-1)} \\ \frac{x_i - S_{i(m-1)}}{I_{i(m-1)} - S_{i(m-1)}}, & S_{i(m-1)} < x_i < I_{i(m-1)} \\ 1, & x_i \ge I_{i(m-1)} \end{cases} \tag{C3}$$

and

$$I_{in} = S_{in} + a(S_{i(n+1)} - S_{in}) \tag{C4}$$

where i is the number of evaluation factors, j is the number of evaluation grade, S_{ij} (i = 1, 2, 3, …; j = 1, 2, …, n, …, m) is the threshold values of grading level set, here was shared equally between 0 and 1, x_i (i = 1, 2, 3, …) is the values of factors, I_{ij} (i = 1, 2, 3, …; j = 1, 2, …, n, …, m) is the interval transition value of membership function, a is the adjusting parameter.

Appendix D. Obtain the future trend in disturbance factors based on the Dinamica EGO model

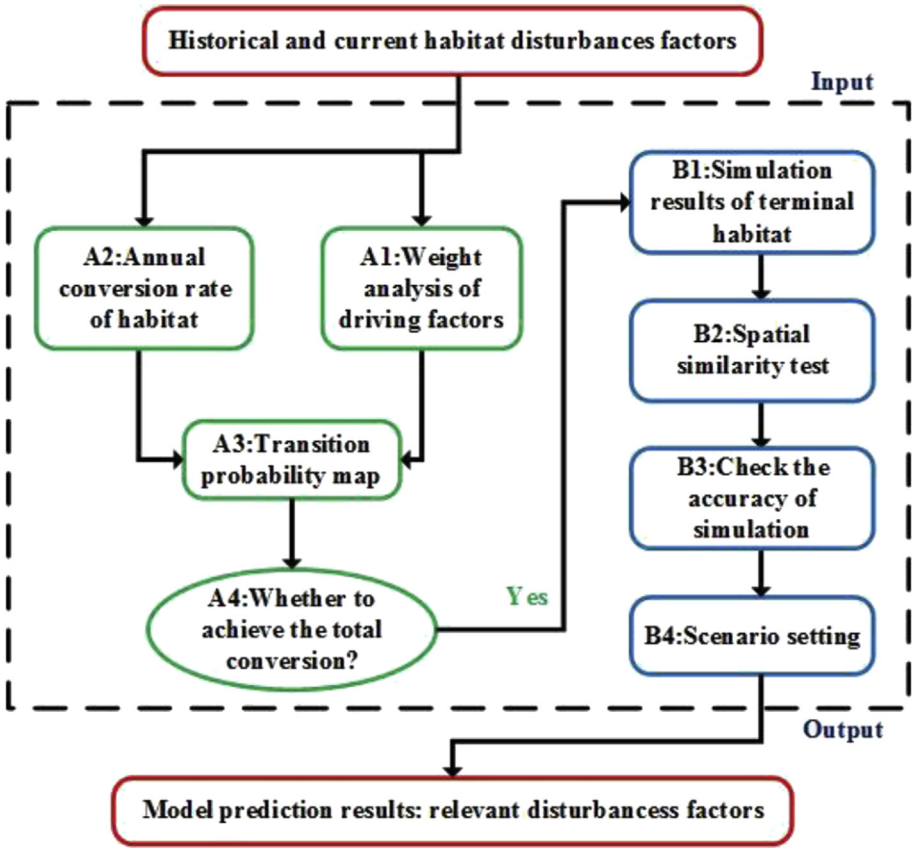


Fig. D1. Dinamica software analysis process.

The Dinamica software analytical process can be divided into two parts: evidence weights for calculating spatial transition probabilities (A1-A4) and simulations to predict trends in disturbance factors (B1-B4).

In this process, we adapted the "Weights of Evidence" method, a Bayesian approach traditionally used by geologists to identify areas that favour geologic phenomena, to calculate the empirical relationships among selected spatial variables, which are represented by grey-tone maps, with respect to changes in the form of urbanization and road expansion. The weights represent the influence of each variable on the spatial probability of a transition $i \Rightarrow j$ and are calculated as follows.

$$\mathrm{O\{D|B\}} = \mathrm{O\{D\}}\frac{P\{B|D\}}{P\{B|\overline{D}\}} \tag{D1}$$

$$\mathrm{logit\{D|B\}} = \mathrm{logit\{D\}} + W^{+} \tag{D2}$$

where $W+$ is the weight of evidence of occurring event D, given a spatial pattern B. The spatial post-probability of a transition $i \Rightarrow j$, given a set of spatial data, is expressed by the following equation:

$$\mathrm{P(i\Rightarrow j(x,\ y)|V)} = \frac{e^{\sum W_{i\Rightarrow j}}}{1 + \sum_{i}^{j} e^{\sum W_{i\Rightarrow j}}} \tag{D3}$$

where V is a vector of k spatial variables, measured at location x, y and represented by its weights W^{+}_{1xy}, W^{+}_{2xy}, …, W^{+}_{kxy}.

As a result, the spatial relationships calculated by the Weights of Evidence method are used to parameterize and calibrate the simulation model with respect to the spatial configuration of the changes.

Appendix E. The weight of each factor for Charadriidae and Anatidae

Evaluating factors		Weight	
		Charadriidae	Anatidae
Habitat importance	Aquaculture ponds u_1	0.0781	0.0844
	Water storage areas u_2	0.0781	0.1125
	Drainage channels u_3	0.0781	0.0563
	Intertidal marshes/intertidal forested wetlands/inland marshes u_4	0.0938	0.0984

	Proportion of shallow water u_5	0.0781	0.0703
	Irrigated land u_6	0.0561	0.0502
	Forest and grassland u_7	0.0463	0.0502
	Specific shelter plant (*Phragmites australis*) u_8	0.085	0.0837
	Benthic biomass (tidal flats width) u_9	0.0622	0.0428
	Benthic biomass (soil type) u_{10}	0.0622	0.0428
	submerged vegetation in ponds u_{11}	0.0752	0.1102
	Salt marsh/marsh vegetation (*Scirpus mariqueter*) u_{12}	0.1164	0.1259
	Tidal creek density u_{13}	0.0902	0.0724
Habitat disturbances	Urbanization (2005–2015) u_{14}	0.30	
	Road density (2005–2015) u_{15}	0.225	
	Wind power farm u_{16}	0.30	
	Coastal reclamation (2005–2015) u_{17}	0.075	
	Invasive introduction (*Spartina alterniflora*) (2005–2015) u_{18}	0.0667	
	Rate of sea level rise (1980–2015) u_{19}	0.0333	

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